Alternative insurance indexes for drought risk in developing countries

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Abstract

The paper compares the risk coping potential of insurances that are based on indices derived from weather (rainfall and temperature) data as well as from crop model and remote sensing analyses. Corresponding indices were computed for the case of wheat production in the Aleppo region of northern Syria, representative for agricultural production systems in many developing countries.

The results demonstrate that weather derivatives such as the rainfall sum index (RSI) and the rainfall deficit index (RDI) have a very good potential for coping with risk in semiarid areas.

Crop simulation model index (CSI) on the other hand could serve as an alternative to RSI and RDI when historical farm yiyeld data is not available or not reliable. In such cases we simulated historical yields using the CropSyst cropping system simulation model.

Remote sensing data could be used to establish index insurances where weather stations are sparsely located and (daily time step) weather data thus not available. The study analyzes two indexes estimated from the Normalized Differential Vegetation Index (NDVI): (1.) the farm level NDVI (FNDVI) and (2.) the area level NDVI (ANDVI). FNDVI may have a very high potential for securing farm revenues, but may be prone to moral hazard since farm management changes and subsequent gains or losses in crop production are directly revealed by the NDVI when high resolution images are used. Therefore, we recommend ANDVI for developing countries since the index is estimated for the whole agricultural zone similar to traditional area-yield insurances.

Keywords: risk management, index insurance, alternative index, CropSyst, NDVI

1 Introduction

Changing rainfall patterns increase the vulnerability of farmers in developing countries under semiarid climatic conditions. Exposure to climate change affects the livelihoods of the rural population and challenges the food security and economic development especially of those countries where the share of agricultural production in GDP is significant. Risk coping options in these countries are limited due to the lack of sufficient financial resources to invest in technological improvement at farm level as well as in the agricultural sector level. Moreover, risk-averse farmers might prefer to spend less on fertilizers and cut their expenses on improved seed varieties when confidence about the returns of such investments is low (Barnett et al., 2007). Agricultural insurances against yield loss/failure could play an important role under these conditions as they would allow transferring risk to agricultural insurance markets and thus increase the confidence of farmers and facilitate their investment into agricultural production in general (Bryla and Syroka, 2007). Therefore, agricultural insurance in the developing countries may have a positive influence on agricultural production beyond merely securing farmer's profits (Hazell and Hess, 2010).

Information asymmetry and high costs associated with field visits and inspections has been shown to be the main problem explaining the lack of insurance markets in developing countries. Index-based agricultural insurances, also known as weather derivatives, have been demonstrated to be promising tools for hedging against climate related uncertainties and thus are considered very suitable for developing countries (Skees, 2008). In short, when insured in such way, farmers receive indemnity when the specified index falls above or below a certain value. The majority of the index insurances are based on weather indexes, which are highly correlated to local yields. Index insurances are based on the factors beyond farmer’s control; this helps to eliminate the problems of moral hazard and adverse selection and reduce the costs for insurance companies by reducing the need for field visits (Bryla and Syroka, 2007).

Existence of systemic risk is one of the major challenges for insurance companies. Systemic risk for instance could be the general drought risk in semiarid agricultural zones where severe droughts might happen in the whole country with a subsequent high number of claims from all over the trading area. Financial reserves of the insurance company might not be enough to pay for all claims unless the insurance companies are linked to reinsurance companies (Xu *et al.*, 2010) or subsidized by the state. Another challenge limiting the widespread adoption of weather derivatives by farmers is the basis risk problem, i.e. the limited correlation between climate and yield. The lack of historical yields and sparsely located weather stations is another constraint for introducing weather derivatives in developing countries.

The objective of this study is to analyze the risk coping potential of alternative indexes in developing countries under conditions of data scarcity. The paper has two specific objectives: (1.) explore the applicability of crop simulation model indexes for semiarid areas where historical yield records do not exists; (2.) investigate the possibility of using high resolution remote sensing images in order to reduce the basis risk problem for regions with little or no weather stations within or nearby.

2 Basis risk and alternative indexes

Rainfall and temperature based index products are currently entering the insurance markets in developing countries (e.g. India, Mongolia). Usually, the risk transfer potential of the weather derivatives contract is determined by the stochastic dependency of the index and farm level income. The problem of basis risk arises when purchased index insurance does not highly relate to farm yields (Hess and Syroka, 2005). Then, it could happen that the farmer who purchased the index based insurance obtained losses, but the index value did not reach the strike value, and the farmer does not receive an indemnity payment. One of the reasons for poor correlation could be the location of the farm far from the weather station (e.g. Odening et al, 2007, Hazell et al., 2010). This is the case in heterogeneous agro-ecological environments where weather stations are sparsely present (Hazell et al., 2010). Similar problems might be observed with area-yield contracts in regions that are exposed to diverse microclimates, such as for instance in mountainous areas. Developing countries are particularly affected: often weather stations are rare, a complete area-coverage absent and/or access to (full) data not given. Moreover, reliability of weather data may be questionable since many weather stations in these countries have been, and may still be, operated manually (Hess and Syroka, 2005). Furthermore, even if historic weather data are available for a particular region, corresponding historic yield data may not, omitting statistical analyses of the data sets and calculation of weather indices. Therefore, the possibility of tackling the basic risk problem by application of low cost alternative techniques is an important topic that needs to be further investigated.

Recent studies related to index-based insurances indicate the possibility of using crop simulation models (Deng et al. 2008) and remote sensing technology to establish indexes, as an alternative to area-yield or weather derivatives. A primary advantage of alternative indexes derived from crop models and remote sensing technologies is the possibility of designing the index under conditions of absent, but otherwise crucial, yield or weather data.

2.1 Crop simulation models

A crop simulation model is a computer program that mathematically simulates the growth of a crop based on its particular response to weather, soil and nutrient dynamics and management aspects. Once properly calibrated for a certain agricultural environments, crop models provide a systemic approach for evaluating the impact of climate and management practices. Common usage of these models cover the analysis of crop performance under different fertilization, irrigation and other management conditions (e.g. sowing dates, tillage, etc.), growth on different soil types as well as the performance of crops under different weather conditions (e.g. climate change).

The possibility of exploring the impact of different weather conditions provides the opportunity for extending the application of crop models also to index insurance product development and application. Deng et al. (2008) used the CERES-Maize simulation model within the Decision

Support System for Agrotechnology Transfer (DSSAT) modeling framework, to compute alternative indexes for securing maize production risk in the USA. They highlighted the potential usage of crop models in estimation of the area-yields in USA counties where county level yield data are missing. A more recent study of Deng et al. (2010) compares the risk management capacity of crop simulation model generated index with the area-yield index under conditions of risk caused by temperature changes.

The potential of crop simulation model indexes for semiarid, developing countries has not yet been investigated. Thus, by comparing the results of crops model derived indexes with traditional weather derivatives as well as remote sensing derived indexes, our study contributes to the (yet sparse) existing literature.

2.2 Remote sensing indexes

The vegetation growth analysis with the usage of (satellite based) remote sensing technologies is one of the intensively investigated fields during the last decades. One of the important developments in this field is the possibility of estimation of crop yields (Hayes and Decker, 1996; Mika et al., 2002; Prasad et al., 2006, Mkhabela et al., 2005). Correlation between county yields and estimated yields ranges between 0.5 and 0.8 in most of the studies (e.g. Hayes and Decker, 1996; Prasad et al., 2006) and recent development indicate the possibility of estimating yields with less than 6 percent of error (Ren et al., 2006).

The possibility of estimating yields by remote sensing gives the opportunity of establishing alternative indexes to the existing rainfall and temperature indexes. The Normalized Differential Vegetation Index (NDVI) is one of the most often used indexes in remote sensing to estimate yields (Hayes and Decker, 1996; Mika et al., 2002; Prasad et al., 2006, Mkhabela et al., 2005). It had been proposed that the NDVI would be a suitable index for insurance purposes (Ceccato et. al., 2008).

There are a few pioneer applications of remote sensing data for index insurances. Chantarat (2009) used NDVI as an index to insure livestock mortality in Kenya. Similarly, Mude *et al.* (2010) used NDVI data to establish an index-based livestock insurance aimed at protecting the pastoral populations of Northern Kenya. Ephias et al. (2010) tested the potential use of remote sensing data while analyzing the relationship between NDVI and historical maize and cotton yield data from nine districts in Zimbabwe.

Most studies applied coarse resolution satellite images; Chantarat (2009) used 8 km resolution satellite data and Diku et al. (2009) used remote sensing images with between 11 and 25 km resolutions. Thus, there is a need to improve the existing knowledge on the application of remote sensing data in insurance studies, by investigating the possible use of higher resolution images (Ceccato et. al 2008). Our study contributes to the ongoing research on the usage of remote sensing image in index insurance while looking at opportunities and challenges of using remote sensing data with finer resolution.

3 Conceptual framework

3.1 Fair premium and indemnity payment estimations

Rainfall and temperature based indexes are the most-often used indexes. Indemnity payments are received when rainfall or temperature falls below specified levels. They often take the form of option contracts (Berg and Schmitz, 2008). Payoff can be estimated in case of long put option as:

$$A = VMax[0, (I - x)] \tag{1}$$

According to Equation 1, farmer receives payment equal to the difference (I-x) multiplied by the tick size (*V*) if the index (*x*) falls below the strike level (I) (Berg and Schmitz, 2008). For example, area-yield farmers may receive an indemnity payment when actual area-yield (x) falls below the specified level (e.g. average area-yield estimated from historical data) of the area-yield index (I).

The fair premium (P_f) can be estimated by multiplying expected value of the payoff (E(A)) by the discount factor (e^{-rd}) (Berg and Schmitz, 2008). It can be written as:

$$P_f = e^{-rd} E(A) = e^{-rd} VE(Max[0,(I - x)]) \tag{2}$$

where r is the interest rate over the duration d.

Equation 2 can be estimated according to the burn analysis (Odening et al., 2008) as:

$$P_f = e^{-rd} \left[\frac{1}{n} \sum_{\tau=1}^{n} A_t \right] \tag{3}$$

Establishment of an index insurance product and identification of its fair premium requires three main steps: (1.) collecting long term yield and weather data; (2.) indentifying the index value and payoffs for each year; and (3.) calculating an average payoff and discounting for the risk free interest rate (Odening et al., 2008).

The total net revenue per hectare under conditions of purchasing the index-based insurance contract can be estimated as:

$$W_p = yp_y + VMax[0,(I - x)] - P_f \tag{4}$$

Finding an index that is highly correlated with yields is the most important step in designing the index-based insurances.

3.2 Estimation of the weather derivatives

The relationship between the index and the farm level yield need to be analyzed in order to identify the suitability of the data for index insurance. The relationship between yield and index can be defined as:

$$Y_\tau = I_\tau + \varepsilon_\tau \tag{5}$$

Where, Y_τ is a farm level yield and I_τ is insurance index and E_τ is an error term and τ is the index for the years. The Rainfall Sum Index (RSI) and Rainfall Deficit Index (RDI) used in Odening et al. (2007) and Bokusheva (2010) were considered as suitable indexes in the scope of this study due to high risk associated with rainfall in the case study region as discussed in the Chapter 4.1. A simple linear function is used in the scope of this study which can be presented as:

$$I_\tau = \beta_0 + \beta_1 X_\tau \tag{6}$$

where X_τ is weather variable, such as temperature or rainfall.

The Rainfall Sum (RS) parameter during the vegetation period is estimated as:

$$RS_\tau = \sum_{t=1}^{n} R_{\tau t} \tag{7}$$

where, t is the days during the vegetation period and $R_{\tau t}$ is the daily rainfall.

Another weather parameter known as rainfall deficit (RD) parameter is estimated according to Odening et al., (2007) as:

$$RD_\tau = \sum_{s=1}^{n} [\min(0, R]_{\tau s} - R^{min}) \tag{8}$$

Where index *s* denotes the weeks during the vegetation period and R^{min} is the minimum weekly rainfall requirement for plant growth. Xu et al. (2007) sets the value of R^{min} to 7.4 mm since it optimized the correlation between the index and the yield. In the scope of this study, R^{min} is defined according to the crop water requirement known as FAO-56 crop evapotranspiration, ET_c, which is:

$$ET_c = K_c\, ET_o \tag{9}$$

where ET_c is the crop evapotranspiration [mm d^{-1}] defined in detail in Allen *et al.* (1998). Several software packages are available to facilitate calculation of ET_c. We used the CropSyst model (Stöckle et al., 2003) for ET_c calculations.

Allowing for this modificattion, R^{min} in eq. 8 is replaced with average weekly crop evopotranspitaion (ET_c) for winter wheat for the years of 2001-2010. The equation above takes the following form:

$$RD_\tau = \sum_{s=1}^{n} [\min(0, R]]_{\tau s} - ET_{cs}) \tag{10}$$

The Rainfall sum index (RSI) is estimates by replacing X_τ in equation 6 with RS_τ in equation 7. Similarly, rainfall deficit index (RDI) is estimated replacing X_τ in equation 6 with RD_τ in equation 9. CR and RD are measured in millimeters and yield is measured in kilograms.

An estimation of RSI and RDI index is not possible without long term daily weather and seasonal yield data.

4 Application

4.1 Case study site

The risk coping potential of weather derivatives and alternative indexes was tested exemplarily for winter wheat production in northern Syria, with around 340 mm of total annual rainfall. This region is representative in terms of climate and soil as well as agricultural management practices for semiarid, rainfed Mediterranean agro-ecozones. Uncertainty of rainfall is the main source of risk to farmers in this region. Furthermore, ongoing and future predicted changes in rainfall amounts and patterns – towards "more dry and more extreme" – is increasing this risk. For example, droughts in years 2007 and 2008 were reported to be the worst in recent history. As a consequence, average country level yields of wheat, barley, lentil and chickpeas reduced by 79% in the rainfed areas (UN, 2008). The eastern part of Syria was most severely impacted. More than 150,000 households (around 750,000 people) completely lost their harvest (UN, 2008). Addditionally, small-scale farmers may suffer beyond the drought year itself, as their financial situation may no longer allow buying (all) seeds and other inputs needed for the following season (Wattenbach, 2006). Traditional risk management options of Syrian farmers often fail due to the severity of the drought, and new policies for improving risk coping potential are needed.

Winter wheat is usually planted in November-December at the onset of the (winter) rainy season and harvested by the end of May, beginning of June. Winter wheat, as well as all other major winter crops in northern Syria, is mainly cropped under rainfed conditions. Irrigation may occur, but is often limited to the summer-autumn cropping season, if applicable (depending largely on the availability of irrigation water). Irrigated systems however are not considered in the scope of this study.

For the calculation of the weather derivate indexes, farm yield data of conventionally, rainfed cropped winter wheat fields (excluding research site with specific management) and daily metrological data was obtained for the research station of the International Center for Agricultural Research in the Dry Areas (ICARDA) located 30 km south of the city of Aleppo in northern Syria.

4.2 Crop simulation model based indexes

For the calculation of the first alternative insurance index, i.e. the index based on crop simulation model outputs of yield, the CRopping SYSTems simulation model CropSyst was used. CropSyst is a multi-crop, daily time step, dynamic deterministic, mechanistic simulation model. Its characteristics are described in detail by Stockle et al. (2003). A number of studies with CropSyst have been documented in literature (e.g. Djumaniyazova *et al.* 2010, Sommer *et al.* 2010). CropSyst is freely available and frequently updated (http://www.bsyse.wsu.edu/cropsyst). It was calibrated to winter wheat using the above-mentioned meteorological data, as well as data on soils and crop management (planting date, tillage, fertilizer application). CropSyst simulates the crop growth on daily basis and therefore daily climate data is a crucial requirement for the simulations. Crop management practices (e.g. fertilized, planting dates) were kept constant at local averages when simulating the historical yields. Only weather parameters were used as changing factors over years. Thus, the simulated yields explain the influence of the weather variation during different years without on-farm risk coping options.

Outputs of CropSyst are manifold, among others comprising daily crop growth parameters (e.g. biomass accrual, leaf area index, evaporation, transpiration), levels of daily crop stress in response to water, (cold/hot) temperature, nitrogen and/or salinity stress. Results may be of seasonal nature or seasonally aggregated, such as harvest index, yield and biomass. Simulated seasonal (annual) yield, thoroughly calibrated against observed yields (Sommer *et al.* forthcoming, Hussein *et al.* forthcoming), was used in the scope of this study, where insurance payments could be based on simulated yields. Other parameters produced by CropSyst such as daily temperature-, water- and N-stress stress were used to explain their influence on crop yields.

4.3 Remote sensing based indexes

With regard to the remote sensing based insurance index, we relied on the Normalized Difference Vegetation Index (NDVI). The NDVI is a measure of greenness density of the vegetation. The greenness itself is related to total biomass and thus to a large extent also to grain yield

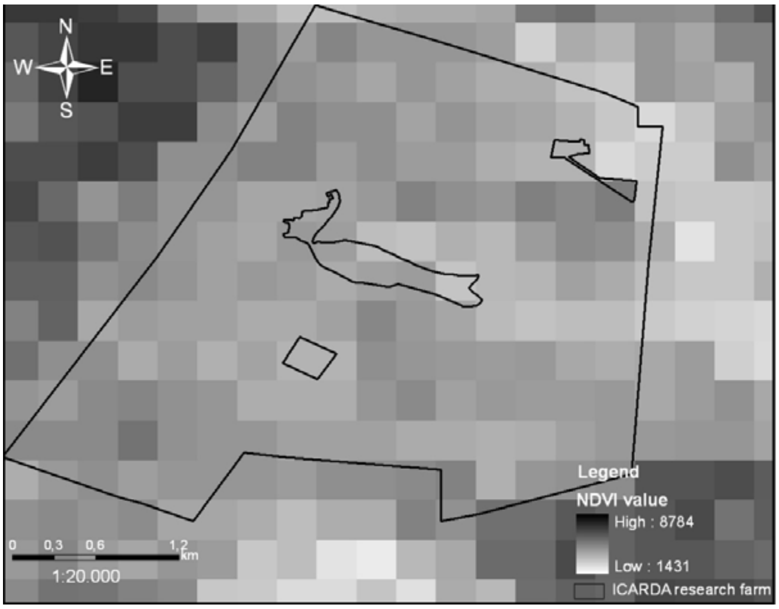

Figure 1: 250m resolution MODIS NDVI data of the case study farm for April 2006

It was derived from daily 250 m resolution MODIS satellite red (RED) and near infrared (NIR) reflectance data averaged temporally over 16 days:

$$NDVI = \frac{NIR - RED}{NIR + RED} \quad (10)$$

NDVI data is usually an index ranging between 0 and 1. Low vegetation growth is close to zero and high biomass if close to one. MODIS NDVI data were obtained for the years 2001-2010. Only March, April and May data were considered in the analysis since these are the critical crop growth periods in the selected location. NDVI data of the area of the case study farm is considered in estimating farm level NDVI (FNDVI) insurance (Figure 1).

The case study farm consisted of 127 grids of a resolution of 250 m. Seasonal averages (March-May) of NDVI from these fields were considered in the analysis.

Farm level NDVI (FNDVI) insurance was estimated with substituting X_τ in equation 6 with seasonal average NDVI from the 127 grids. Moreover, area-NDVI insurance (ANDVI) was estimated for the same agro-ecological zone (AEZ), following the AEZ-classification suggested by De Pauw (2004), in which the case study farm was located (Figure 2). This AEZ consisted out of 3198 250 m resolution grids. ANDVI insurance was estimated with substituting X_τ in equation 6 with seasonal average NDVI of these 3198 grids.

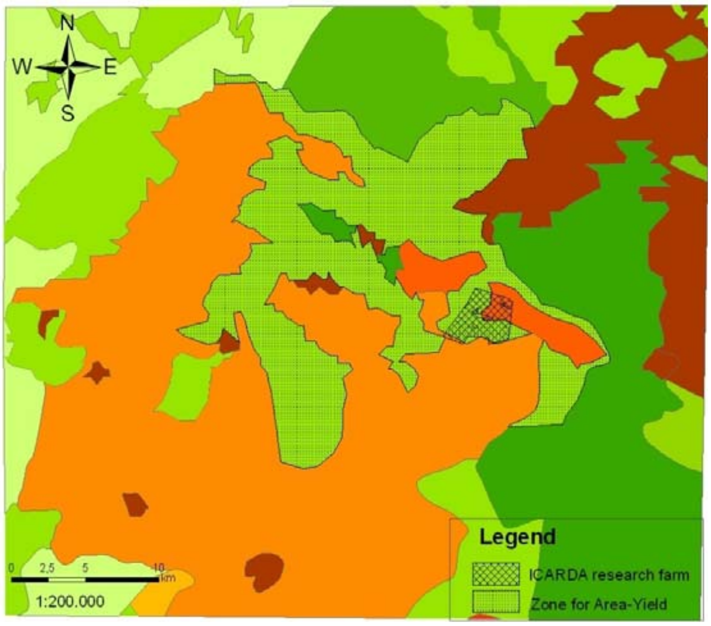

Figure 2: The agro-ecological zone for the estimation of the ANDVI (De-Pauw, 2004, **modified).**

5 Results

5.1 Weather derivatives

Correlation of yield and the rainfall sum (RS) was equal to 0.77 and the yield rainfall deficit (RD) correlation was equal to 0.85. Regression parameters of the RSI and RDI indexes are presented in Table 1. Coefficient of determination (R^2) was equal to 0.59 for the RSI model and 0.72 for RDI model.

Table 1: Estimated parameters of the weather derivatives; standard error in parentheses

Parameters	RSI	RDI
R^2	0.59	0.72
Slope (β_0)	-379,3 (0.678)	11342,9 (0.000)
Intercept (β_1)	9.2(0.009)	-12,3 (0.002)

The p values of all coefficients presented in Table 1 was significant except the slope of the RSI model. A positive slope of the RSI model indicates a positive correlation between CR (measured in mm) and yield (the higher the CR the higher the yield), and vice-versa.

5.2 *Crop model index*

Figure 2 presents actual and simulated yields by CropSyst for the years of 2001-2010. Correlation between actual yield and simulated yield is equal to 0.78, which was a little higher than the correlation of actual yield and RSI but less than the correlation between actual yield and RDI.

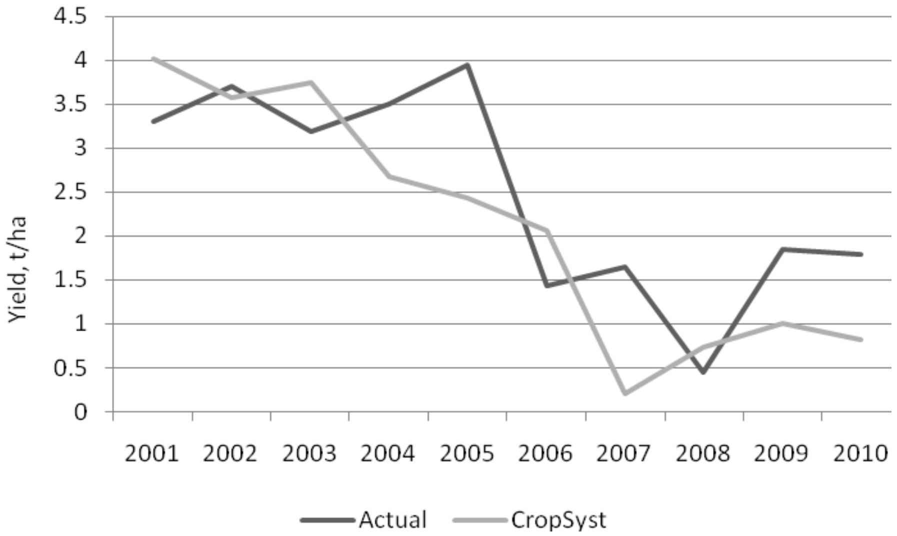

Figure 3: Observed and simulated yield by CropSyst.

Difference between simulated yields and observed yields may be explained by the rather static model setting of keeping the management practices constant for all years, whereas this is not the case in reality. For example, farmers adjust the planting date in response to the onset of the rainy season, which may vary by several weeks from year to year. This was not considered in the simulations, since the objective of the simulation was to consider the impact of weather variation only.

5.3 *Remote sensing indexes*

Correlation between FNDVI and yield was equal to 0.79 and correlation between ANDVI and yield was equal to 0.57 indicating some potential of these indexes for explaining yield variations. The positive signs of the slopes of both models indicate increasing yield with increasing value of NDVI (Table 2).

Table 2: Estimated parameters of FNDVI and ANDVI models

Parameters	FNDVI	ANDVI
R^2	0.62	0.32
Constant (β_0)	-5754,8 (0.035)	-6582,9 (0.194)
Intercept (β_1)	2768,1 (0.007)	2836,9 (0.085)

The predictive power of the parameters of the ANDVI model was low, which we attributed to two main factors. The first is the relative short period for which actual yield and remote sensing data was available. The second was due to the map, which was underlying the AEZ characterization

(De-Pauw et al., 2004), which indeed was from 1990 and thus probably somewhat outdated for the scope of this study.

5.4 Risk coping potential of traditional and alternative indexes

Fair premium, indemnity payments and other parameters of traditional and alternative index insurances were estimated according to the methods described in chapter 3.1. The price for winter wheat was assumed to be stabile and set to one. The strike level for all indexes was set to 2483 kg, which is the average yield of the case farm for the considered period. The following table demonstrates the mean revenues without insurance and with five different index insurances.

Table 3: Returns without insurance and with index insurances

Parameter	Without insurance	RSI	RDI	CSI	FNDVI	ANDVI
Fair premium	N/A	382,5	381,8	580	344	250,6
Mean	2483	2483	2483	2483	2483	2483
St. Dev	1185,7	815,7	749,7	697,1	783,4	903,7
Min	450	1108,1	1468,1	1095,83	1505,9	1543,3
Max	3950	3620,1	3568,1	3244,5	3605,9	3779,3

All insurance schemes had a potential of reducing the standard deviation of the revenue for a certain amount of payment. The lowest fair premium was achieved by the ANDVI index, with a standard deviation being higher than those of the other indexes. The lowest standard deviation was achieved for the CSI. On the other hand, this was the index that had the highest insurance premium. Information about the utility function of the farmer is needed in order to rank these indexes.

6 Discussions

The results demonstrated that risk coping potential of traditional index insurances such as RSI and RDI is very high for the dry areas where water availability is the main constraining factor for crop growth. RDI could be very good tool for drought risk management when possibility of estimating crop evapotranspiration exists. Otherwise, RSI could be also used since the considerable reduction of the standard deviation was also achieved under this insurance scheme. However, the lack of long term yield records in developing countries may create difficulties in establishing a suitable index insurance program.

Usage of crop simulation model could fill the gap of yield data scarcity that is relevant in developing countries. The performance of weather derivatives and crop simulation model index presented in table 3 cannot be directly compared without knowing the risk aversion of the decision makers. However, the analysis has shown that crop simulation model derived yield indexes could serve as an alternative to weather derivatives since they have the potential of reducing the standard deviation and secure a two times higher minimum income than farming without insurance. Another potential advantage of CSI could be reducing the need for collecting farm yield which is very time consuming and costly. However, some information on the farming practice is still needed to calibrate the crop simulation model. Long term yield data could be simulated after the calibration process, as it was demonstrated in the previous chapters. Another advantage of using a sophisticated crop simulation model could be the possibility of taking the yield-response difference under heterogeneous agro-ecological (texture, soil humus content, groundwater level) environments which might help to reduce the basis risk.

Crop simulation model requires daily weather data similar to weather derivatives and CSI and yield dependency is expected to reduce when going to locations far from the weather station similar the finding of Odening et al. (2007).

FNDVI and ANDVI indexes reduce the need for weather station data since crop performance is directly observed with the remote sensing images. Both FNDVI and ANDVI have a potential of reducing standard deviation of income when compared to the situation without insurance. Usage of finer resolution images could increase the accuracy at farm level, which we assume is responsible for the higher correlation between yield and FNDVI than yield and ANDVI. However, it is important to mention that farming practices such as seed rate and fertilization has also impact on the farm yields which is also reflected in the estimation results. Therefore, an insurance based on FNDVI is not free from moral hazard. This has not been discussed in the available literature on the issue (Chantarat, 2009; Mude et al., 2010; Ephias et al., 2010) since these only considered usage of low resolution images. An area-yield, remote-sensing derived index such as the ANDVI is free from moral hazard and thus may be used alternatively. Remote sensing derived area-yield index has several advantages when compared to conventional area-yield indexes in developing countries. One of the most important aspect is the cost and time efficiency when estimating the area-yield with remote sensing technology. Usually estimation of the area-yield requires very long time since farm yields should be collected from many farmers, instead it could be estimated from the remote sensing data usually freely available only short after the harvest. Available literature has already demonstrated that the yield could be estimated even 40 days before the harvest date according to the biomass available on the field. Moreover, area-yield could be estimated not on administrative level but on agro-ecological zone level which helps to reduce basis risk due to considering the areas with the same growth environments. However, one of the challenges in application of remote sensing data could be the demand for yield data for calibration purposes.

Conclusions

The traditional weather derivatives such as RDI and RSI may be still robust option to cope with weather variation. The usage of weather derivative or alternative indexes needed to de decide according to the local data availability and agro-ecological conditions.

The usage of crop simulation model could serve as an alternative to traditional weather derivatives or area-yield insurance. Calibrated crop simulation models could be used to simulate historical yields in order to estimate risk premiums and indemnity payments when yield data is not available. However, potential gains from the growth model may also have also limited when reliable weather data is not available.

The remote sensing derived indexes could have a good potential for coping with drought risk where long term weather data is not available or weather stations are very sparsely located. Usage of high resolution images may give an option of estimating the on-farm specific index such as FNDVI which is very highly correlated with the farm yields. However the study recommends the usage of ANDVI index due to moral hazard issues with FNDVI. ANDVI may have several advantages over simple area-yield. One of the advantages could be reduced costs of obtaining data and possibility of estimating the yields several weeks before the harvest.

There are certain limitations of the study results that require further research. Analysis and discussion of this paper is suitable for the environments where water stress is most limiting factor. Risk management potential of the alternative indexes for other agricultural systems, such as under supplemental or full irrigation, may differ from the results presented. Improvement of the methodology of identification of zones with homogeneous growth conditions could contribute to better estimation results of ANDVI insurance models. Moreover, analysis of remote sensing data was limited to NDVI, and the suitability of a wide range of remote sensing indexes other than NDVI for insurance purposes is worth further research.

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